

Perceptually Validated Analytical BRDFs Parameters Remapping

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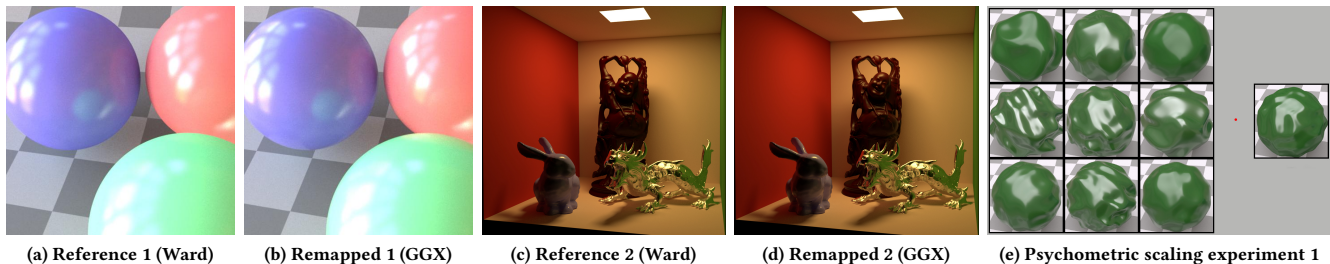


Figure 1: In (a-b) and (c-d) some examples of source and our remapped renderings. In (e) the interface of one of the psychometric scaling experiments.

ABSTRACT

The need to manually match the appearance of a material in two or more different rendering tools is common in digital 3D product design, due to the wide range of tools and material models commonly used, and a lack of standards to exchange materials data. Since the effect of BRDF parameters on rendered images is non-uniform, visually matching to a reference is time consuming and error-prone. We present an automatic BRDF remapping technique to match the appearance of a source material model to a target, providing a mapping between their parameter spaces. Our framework, based on Genetic Algorithm optimization and an image space similarity metric, provides a faithful mapping among analytical BRDFs, even when the BRDF models are deeply different. Objective and perceptual evaluations confirm the efficacy of the framework.

CCS CONCEPTS

• **Computing methodologies** → **Machine learning**; **Rendering**; **Reflectance modeling**; **Perception**;

KEYWORDS

BRDF model, Perceptual validation, Materials, Surface perception

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1 INTRODUCTION

The appearance of a virtual material depends on the underlying BRDF model implementation; the same material model can be implemented differently in different rendering tools [Sztrajman et al. 2017] and even between different versions of the same renderer, thus affecting the appearance of the final renderings.

In many contexts involving the development of 3D content, it is common to make use of a range of different tools, however there is no widespread standard to facilitate exchange of material models and data. Therefore, given a material represented with a specific model (*source*), not available in a different rendering tool or implemented differently, a digital artist is left with the only option to manually match the appearance of the source using a model available in the rendering tool / model in use (*target*), i.e. manually finding a mapping between the set of source parameters and the target parameters. Such a manual *remapping* does not have any actual reference point in terms of what parameters to use, and it is mostly based on a pure guess. Selecting the appropriate parameters value for a BRDF model is not straightforward, since they are often not intuitive and their effect is non-uniform [Ngan et al. 2006].

We propose an automatic image-based solution to find the best mapping between the source and target models parameter spaces (*parameters remapping*). Given a few renderings with the source BRDF model, we use Genetic Algorithm (GA) optimization to find a set of parameters in the target BRDF model, such that an object rendered using the optimized parameters for the target model matches

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appearance of the source one. The genetic algorithm is driven by a computational metric defined in the image space, which compares renderings of a scene under a specially designed incident lighting.

Related Work. [Ngan et al. 2006] defined an image-based metric to measure the distance between BRDFs. The metric is used to navigate variations within a model and also in the space of BRDFs. The remapping of BRDF parameters has been addressed by [Sztrajman et al. 2017]. Starting from a user-provided guess of the parameters for the target model, a nonlinear optimization algorithm tries to find a set of parameters to minimize a L^2 metric. Unlike [Sztrajman et al. 2017], our framework does not require an initial guess of the target parameters, enabling the use as a “black-box”. Moreover, the GA allows us to set the desired resolution for the parameters involved in the remapping, and to employ more complex error metrics.

2 PROPOSED FRAMEWORK

We aim at BRDF models defined as a sum of a diffuse and a specular terms, the most common analytical models [Guarnera et al. 2016].

The core of our solution is a GA, with access to a renderer implementing the target BRDF model. GAs can be used when no information is available about the gradient of the function, which does not need to be continuous nor differentiable and provide good results even when the function has several local minima.

The input to our system is a set of High Dynamic Range (HDR) renderings of a reference scene, along with the list of parameters used for them. The GA starts from a random guess about the parameters of the target model and requests to the target renderer a set of renderings with these parameters; driven by the Fitness Function, which measures the visual difference between the source and target renderings, the optimization requests a new set of parameters to test, and a new set of renderings is produced; this process is repeated until the best mapping is found.

The fitness function computes a L^2 metric in image space, and it is tunable by means of additional parameters, to better address human perception and account for edges and gradient information; in the basic configuration it is equivalent to the ΔE_{76} color difference.

To derive a monotonically non-decreasing remapping, given a set of m -tuples of source parameters to be remapped towards a set of n -tuples in the target space, the GA is constrained to explore variations in only one source parameter at a time, in a monotonically increasing fashion. The starting point of the search in the target parameter space makes use of previously remapped parameters, when available. The whole source parameter space is sampled, and fitting module takes care of finding a smooth, analytical relationship between the source and the remapped parameters.

The reference scene used to learn the mapping is illuminated by an ad-hoc environment map, designed to allow a clear analysis of the surface response to the lighting at different color bands, improving the estimation of roughness, specularly and anisotropy.

3 EXPERIMENTS AND RESULTS

We discuss the remapping between two very different models, from the Ward BRDF (source) to the BRDF component of the GGX model [Walter et al. 2007] (target). Such a case study is relevant also in the Human Vision and Perception field, where empirical models are widely used [Fleming 2014; Toscani et al. 2017].

The Fresnel effect has a great impact on the appearance of a dielectric, in particular at grazing angles. It implies that source and target renderings tend to differ towards the objects’ contours, since the source model lacks the Fresnel effect. Hence, in this case the mapping is learned by weighting less the objects’ contour areas.

For a set of test scenes with complex geometry (see Figure 1 (a-b) and (c-d) for some examples), we compared the original source renderings with our remapped ones. The resulting Normalized Root Mean Square Deviation is, on the average, below 2.7%.

We conducted a set of user studies, aimed to establish whether the participants can distinguish between our remapped renderings from the original source ones. The participant’s age ranges between 14 and 71 years old and their expertise in graphics and arts varies from no expertise to professional (15 subjects in total).

The outcome of the user studies was tested for statistical significance using the one-tailed Welch’s t -test, showing that, for a large portion of the parameter space, the observers were not able to distinguish between source and remapped renderings.

To complete the evaluation, we conducted a set of psychometric scaling experiments, using the Psychophysics Toolbox V3 [Kleiner et al. 2007], again covering the parameter space and using natural environment light probes. The first experiment provided an assessment that, from a perceptual point of view, our remapping is the best possible. Ten subjects were presented with a source rendering on the right side of the screen and nine renderings on the left side, in random order (Figure 1(e)). Only one rendering out of the 9 was given by our remapped parameters, whereas the others were rendered using parameters in its reflectance neighborhood, defined in the target parameter space. The task of the observers was to rank the renderings on the left side of the screen, from the closest one in terms of reflectance properties to the source rendering, to the most different. Each session lasted 2–3 hours, covering the whole parameter space. Results show that in the majority of cases the observers ranked the renderings produced by our technique as the most similar to the source ones, confirming the perceptual accuracy of our technique.

An additional scaling experiment confirmed that when observers were able to distinguish source and target renderings, the Fresnel effect was used as a cue, and this effect is visible mainly on shiny, smooth objects towards their silhouette. There was no perceivable difference in the remaining areas of the objects.

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